

Oil Prices and Alternative Energy Stock Performance

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Abstract

In 2007, Irene Henriques and Perry Sadorsky wrote "Oil prices and the stock prices of alternative energy companies," a paper examining the relative importance of oil prices and technology stock performance when determining the performance of alternative energy companies. Using a vector autoregression model, they showed that oil prices were not all-powerful when determining alternative energy performance, and indeed, technology appeared to be considerably more important. We have extended the Henriques/Sadorsky model to include a breakdown of various types of alternative energy companies to show that while certain types of alternative energy companies do indeed follow this model of more compelling reactions to technology stock performance than oil price, certain types of alternative energy companies defy the aggregate pattern that Henriques and Sadorsky discovered.

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Introduction

Alternative energy is emerging in the marketplace, and its growth, and what drives that growth, is of great interest to policy makers, economists, and everyone following current events in environmental, economic, and policy related fields. It has long since been thought that oil prices have an effect on the performance of alternative energy stocks, as the substitution effect will drive up

the price of alternative energy stocks when oil becomes more expensive, buoying the alternative energies as they become more popular at the expense of conventional energies. Henriques and Sadorsky questioned the general wisdom that oil was the all-powerful determinant of alternative energy prices, and in their paper "Oil prices and the stock prices of alternative energy companies," used a vector autoregression to deduce that technology stock performance has a stronger impact on alternative energy companies than oil prices.

However, different types of alternative energy companies play very different roles in the production of energy, with various places in the market. There is reason to suspect that different shocks to the market would affect these different types of companies in different ways. This breakdown of alternative energy, once this broad, all-encompassing category, motivates our extension of the Henriques/Sadorsky paper. Alternative energy is a famously multi-partite policy, with each step of the process of energy generation becoming a key step in innovation and policy. Energy storage is a key issue of solar energy generation, for example, and many other individual steps in energy generation become issues in their own right, thus making a breakdown something that could enrich the Henriques/Sadorsky paper tremendously, with continued and more specified ramifications of interest to those involved in making and evaluating energy policy.

This paper will first outline the data used, of particular interest since we will be constructing data for our breakdown of the Henriques/Sadorsky data. Then we will follow the map laid out by the Henriques/Sadorsky paper, only with more specified variables in addition to the original aggregate variable that represented the performance of alternative energy stock prices.

Data

The data we use is largely the same as the data used in the paper by Henriques and Sadorsky. We use the oil stock prices, the Pacific Stock Exchange Technology Index (PSE), the interest rate, and the S&P index data used in the same form in the Henriques/Sadorsky paper. The PSE index measures the performance of technology companies in the Arca Tech 100 index and is our measure for the performance of technology prices in the marketplace. As in the original paper, we find the weekly data for PSE and oil prices from Datastream, and the interest rate data were obtained from the Federal Reserve Board of St. Louis

(<http://research.stlouisfed.org/fred2/>).

The extension we make to the original paper is to take a closer look at the data in the ECO index. The ECO index, or the WilderHill Clean Energy Index, is an aggregate look at about 40 companies that work in alternative energy in some way. As we have said, the alternative energy field is famously diverse, and there is reason to suspect that breaking down this aggregation will be illuminating. We looked at the companies that comprise the ECO index, and using WilderHill's own divisions, created indices based on each of the following types of companies used in creating the index: renewable energy harvesting, energy storage, cleaner fuels, energy conversion, greener utilities, and power delivery and conservation.

Each index was built up using the stock prices of the companies in each category (as described by WilderHill at www.wilderhill.com). Some stock prices, as we found, were labeled negative, which occurs when no trade takes place for a given stock on a given day. We changed these prices to positive, as this positive number is the average of the bid and asked prices for the day, and is a relevant depiction of the performance of the stock. The prices were found at the Center for Research in Security Prices (CRSP) and weighted as in the WilderHill index to make mini-indices for the categories listed above.

The weighted averages created a mathematical problem as many companies in the index are younger than the index itself, and were only factored into the index starting later. Due to the small number of stocks in each mini-index, there is a significant shock to the index each time a company is added to the index, or drops out. For example, if a company's price declines until it goes under, the index will rise as the smaller price stops being factored in. There are similar effects as new companies are added. This shock is not related to the effect of technology or oil prices (proliferation of alternative energy companies may be affected, but it is not our goal to measure this effect). Therefore, at the introduction or elimination of a stock, we hold the index constant and normalize the weighted index off of that value. This eliminates the extraneous variability in the index due to the shocks of adding or taking away a stock. However, it also limits the weekly variability since the new index value after a stock is added or eliminated is held constant across this change. However, since weekly variability of the index is not nearly the shock of adding a stock, especially for the smaller indices, we are not concerned with this phenomenon - holding the index constant will ultimately aid in getting a close picture of the mini-index's true relevant value.

Prices of Indices

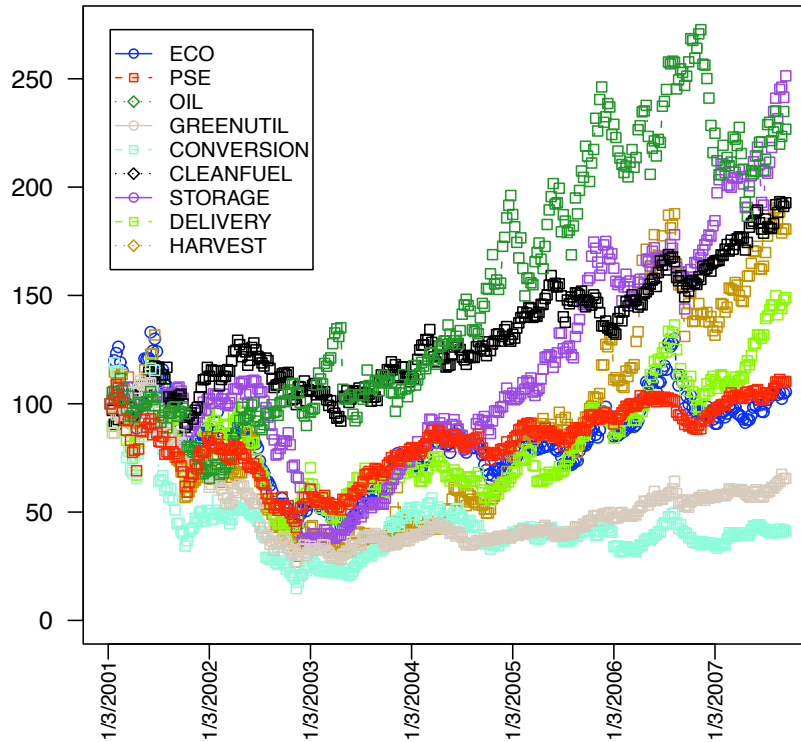


Figure 1: Time Series Plot of ECO, PSE, Oil Price, and Breakdown Indices

In keeping with these modifications, we generate indices called GREENUTIL (GU), CONVERSION (CON), CLEANFUEL (CF), STORAGE (STR), DELIVERY (DV), and HARVEST (HRV) to which we can apply the methods of the original paper to see if the conclusions of the original hold for the various types of alternative energy companies as well as the aggregate ECO.

Time Series and Summary Statistics

Figure 1 shows a time series plot of ECO, PSE, the price of oil, and each of the breakdown indices, with each index/price set to 100 at the origin so all may be shown together and more easily compared. The original paper highlighted the

close correlation of ECO and PSE, as opposed to the less compelling correlation of ECO and oil prices (the correlations were 0.83 and 0.43, respectively). Also, the visual analysis shows similar performance of ECO and PSE, with lower and less frequent highs, as opposed to the very different performance of the oil price, which continues to rise rapidly.

However, these comparisons do not seem to apply to each of the breakdown indices equally. Some of the indices - Green Utilities and Conversion - seem only loosely correlated with either PSE or oil, while the clean fuel index seems more correlated with the price of oil than PSE. Table 1, the table of correlations shows that there is indeed considerable variation in the correlations between each of our breakdown indices and PSE and oil, with some indices showing more correlation in general (Harvest, Clean Fuel, and Storage show high correlation with both) and some showing very little (Green Utilities and Conversion), and only one, Delivery, showing the high correlation with PSE and lower correlation with oil price that we saw with ECO.

	ECO	GU	CON	CF	STR	DV	HRV
PSE	0.83	0.41	0.38	0.75	0.84	0.84	0.85
OIL	0.43	-0.09	-0.22	0.85	0.79	0.57	0.76

Table 1: Correlations between Alt. Energy and oil price/technology

The average returns of each of these indices varies widely, as reflected in Table 2. These do not show, as the ECO aggregate does, returns that align closely with PSE as opposed to oil. The average returns for Storage and Clean Fuel were very high, close to the Oil average return. Green Utilities and Conversion show negative returns, indicating a very weak market for those specific stocks during this time, where Delivery and Harvest indices show returns in between. The Sharpe ratio shows that while ECO, PSE, and the general market (represented by the SP500 market index) were similar, we have a much more profitable oil, clean fuel, and storage market and much less profitable green utilities and conversion markets, with delivery and harvesting slightly outperforming on this risk-adjusted basis.

	ECO	PSE	OIL	SP500	GU	CON	CF	STR	DV	HRV
Mean	0.02	0.03	0.25	0.04	-0.13	-0.27	0.20	0.28	0.12	0.18
Avg Annual	0.84	1.52	12.75	1.98	-6.58	-13.79	10.22	14.35	6.20	9.20
Median	0.20	0.09	0.55	0.10	0.23	-0.00	0.31	0.59	0.00	0.23
Maximum	18.18	13.54	10.62	10.18	13.88	18.31	11.74	11.01	20.55	20.13
Minimum	-13.79	-12.77	-23.59	-7.84	-23.01	-45.89	-12.35	-50.84	-19.58	-47.68
S.D.	4.31	3.48	4.40	2.20	4.30	6.77	2.95	4.66	5.63	6.99
Skewness	-0.03	0.03	-0.71	0.21	-0.83	-1.26	-0.29	-4.05	-0.06	-1.27
Kurtosis	4.14	4.60	5.35	5.76	6.14	10.37	4.75	45.23	4.21	9.95
Jarque-Bera	18.25	35.51	104.94	108.50	175.45	843.30	47.34	25736.95	20.71	762.42
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nobs	334.00	334.00	334.00	334.00	334.00	334.00	334.00	334.00	334.00	334.00
Sharpe ratio	-0.06	-0.05	0.32	-0.05	-0.30	-0.34	0.35	0.35	0.09	0.13

Table 2: Summary statistics for weekly returns

Risk Comparisons

Table 3 shows us the multifactor model of market risk comparisons. The market coefficient shows us that clean fuel and storage are less risky than the general market, while ECO and PSE indices are both around 40% riskier than the market, with green utilities 19% riskier, and conversion over twice as risky, with delivery almost twice as risky and harvesting 59% riskier. These breakdown indices are in general very risky, in line with or more so than the aggregate ECO value. These comparisons, however, are static, and as in the Henriques/Sadorsky paper, we move into a dynamic analysis with the vector autoregression.

	ECO	PSE	GU	CON	CF	STR	DLV	HRV
Constant	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00
Constant t	-0.38	-0.37	-1.09	-1.25	1.52	0.87	0.20	0.28
Market	1.40	1.41	1.19	2.03	0.79	0.77	1.92	1.59
Market t	15.01***	17.08***	10.58***	8.90***	11.17***	5.15***	11.93***	10.20***
Oil	0.11	0.00	0.06	0.09	-0.04	0.12	0.03	0.15
Oil t	3.17***	0.11	1.60*	1.25	-1.37*	2.12**	0.78	1.94**
Rate	0.01	-0.03	0.01	-0.02	0.03	0.13	-0.02	0.01
Rate t	0.19	-1.23	0.10	-0.36	0.61	1.13	-0.38	0.10
Adj R2	0.52	0.79	0.37	0.44	0.36	0.16	0.56	0.26
DW	2.03	2.15	2.16	1.97	2.03	1.79**	2.22	2.29
$F(p)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3: Market risk comparisons from estimating a multifactor model

***, **, * denote a test statistic significant at the 1%, 5%, or 10% level DW is the Durbin-Watson statistic, $F(p)$ is the probability value for an F of all coefficients equal zero

Unit Root Tests

Here we perform unit root tests to find the order of integration of our variables. The tests we perform are the Augmented Dickey and Fuller (ADF) test, the Phillips and Perron (PP) test, and the Kwiatowski-Phillips-Schmidt-Shin (KPSS) tests, as performed in the Henriques/Sadorsky paper. The ADF and PP tests have the null hypothesis of a unit root, and we see that only after inspecting the first differences will we reject the null hypothesis, and therefore the maximum order of integration is order one. We show the ADF test results here, with the PP and KPSS tests presented in the appendix. The KPSS tests, with a null hypothesis of stationary data, is only not rejected once we take second differences, which implies, for Green Utilities, Storage, and Harvest, that 2 integrations are necessary. Therefore we use an order of integration of 2.

Likelihood ratio statistics show that the optimal lag length is 8 for all data except for Green Utilities and Clean Fuel, which use 9.

	ECO	GU	CON	CF	STR	DV	HRV
Levels	-1.494 (0)	-2.03 (0)	-2.82 (0)*	-0.89(0)	0.05(0)	-1.22 (0)	-0.73(0)
1st Diff.	-17.90(0)***	-20.53(0)***	-17.64(0)***	-19.55(0)***	-16.40(0)***	-19.49(0)***	-20.97(0)***

Table 4: ADF Test

DISCUSS WHAT THE NUMBERS MEAN HERE

VAR Results

The goal is ultimately to discover which of a shock to technology stock prices or a shock to oil prices has more of an effect on the dependent variable, which is ECO or one of our breakdown indices. We will use our VAR equation to investigate, and therefore here present our tables to demonstrate the close fit of our VAR models for each of our indices.

As in the original paper, the VAR model on the aggregate ECO index is very strong, with R^2 values consistently over 0.978, and very small standard errors, with high F statistics. This trend continues with each breakdown index, with very high R^2 values consistently in the 0.98 range, with the exception of Conservation, which has a not much lower 0.966 R^2 value in its VAR model. These values, coupled with standard errors in the 0.03 range, are compelling, and allow conclusions to be drawn from the model with regard to shocks to the system.

	LECO	LPSE	LOIL	LIR
R-squared	0.979	0.980	0.990	0.997
Adjusted R-squared	0.976	0.977	0.988	0.997
S.E. Eq	0.039	0.032	0.043	0.04
F-stat	327.8	344.5	675.2	2417.0

Table 5: VAR model fit for ECO aggregate

	LGU	LPSE	LOIL	LIR
R-squared	0.986	0.980	0.991	0.997
Adjusted R-squared	0.984	0.977	0.989	0.997
S.E. Eq	0.039	0.32	0.041	0.035
F-stat	451.5	306.8	657.8	2234

Table 6: VAR model fit for Green Utilities

	LCON	LPSE	LOIL	LIR
R-squared	0.966	0.980	0.990	0.997
Adjusted R-squared	0.961	0.977	0.988	0.997
S.E. Eq	0.060	0.032	0.043	0.034
F-stat	200.8	343.5	685.4	2600

Table 7: VAR model fit for Conversion

	LCF	LPSE	LOIL	LIR
R-squared	0.980	0.980	0.990	0.997
Adjusted R-squared	0.976	0.977	0.988	0.997
S.E. Eq	0.029	0.032	0.043	0.034
F-stat	301.6	312.6	611.1	2286

Table 8: VAR model fit for Clean Fuel

	LSTR	LPSE	LOIL	LIR
R-squared	0.992	0.980	0.990	0.997
Adjusted R-squared	0.991	0.977	0.988	0.997
S.E. Eq	0.045	0.031	0.043	0.035
F-stat	855.5	352.9	679	2456

Table 9: VAR model fit for Storage

	LDV	LPSE	LOIL	LIR
R-squared	0.974	0.980	0.990	0.997
Adjusted R-squared	0.970	0.977	0.988	0.997
S.E. Eq	0.051	0.032	0.042	0.035
F-stat	262.5	344.5	704.6	2393

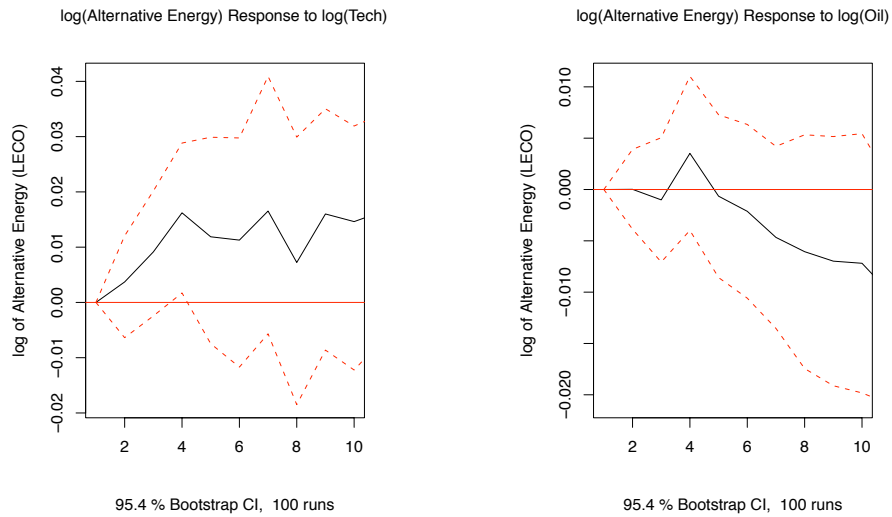
Table 10: VAR model fit for Delivery

	LHRV	LPSE	LOIL	LIR
R-squared	0.986	0.980	0.989	0.997
Adjusted R-squared	0.984	0.977	0.988	0.997
S.E. Eq	0.067	0.032	0.043	0.035
F-stat	499.9	342.5	658.7	2434

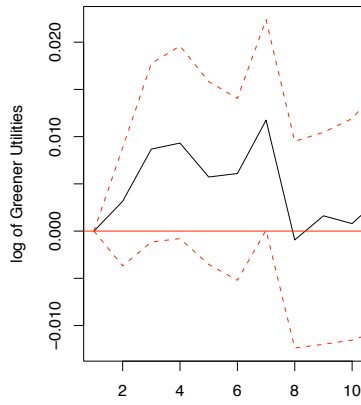
Table 11: VAR model fit for Harvest

Impulse Responses

These graphs below represent what happens to a dependent variable when there is a one-standard-deviation shock to either oil price or technology stock index. We focus on those two covariates as opposed to interest rate and other variables used, as these two are the variables of interest for us, which we wish to compare along the lines of the comparison raised in the Henriques/Sadorsky paper. We see that a shock to technology price yields a more enduring change in ECO than an oil price shock, while Green Utilities and Energy Conversion react in a strong negative manner to an oil shock but not enduringly to a shock in technology price. Clean Fuels, Energy Storage, and Harvesting react enduringly to technology price shocks but not oil shocks. Power Delivery reacts slightly more enduringly to a technology shock than to an oil shock, but not considerably more so. Most of the responses are not significant at the 95% level, with the exception of the response of Harvesting to a PSE shock, Energy Storage to a PSE shock, and Green Utilities to an Oil shock. Even these responses only become significant after several weeks.

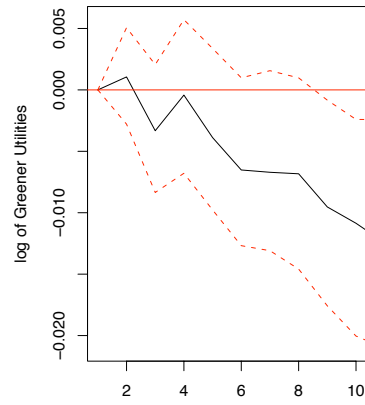


log(Greener Utilities) Response to log(Tech)



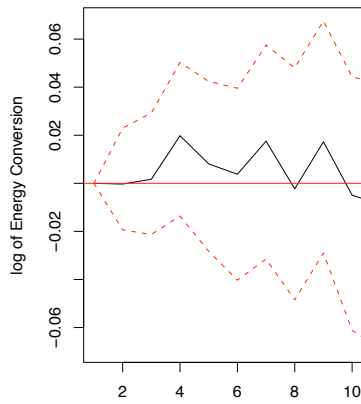
95.4 % Bootstrap CI, 100 runs

log(Greener Utilities) Response to log(Oil)



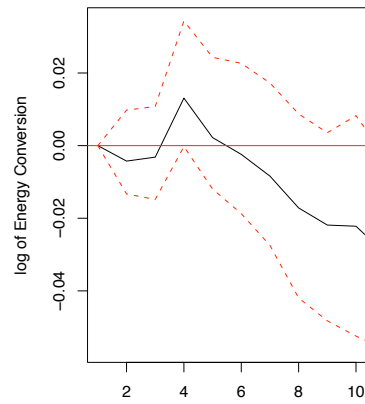
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log(Energy Conversion) Response to log(Tech)



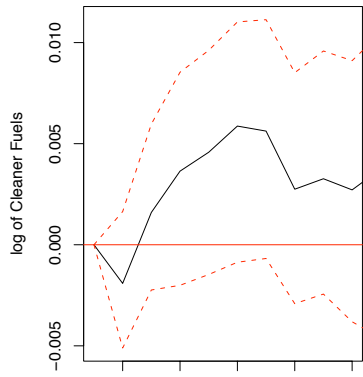
95.4 % Bootstrap CI, 100 runs

log(Energy Conversion) Response to log(Oil)



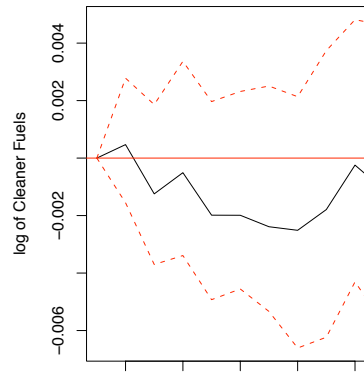
95.4 % Bootstrap CI, 100 runs

log(Cleaner Fuels) Response to log(Tech)



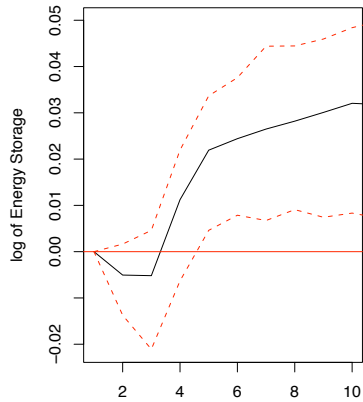
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log(Cleaner Fuels) Response to log(Oil)



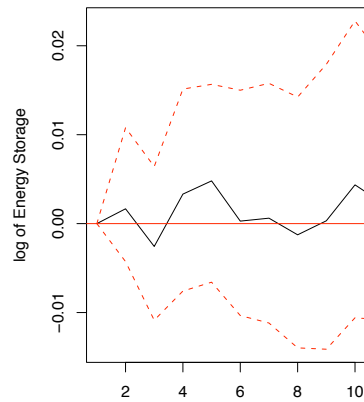
95.4 % Bootstrap CI, 100 runs

log(Energy Storage) Response to log(Tech)

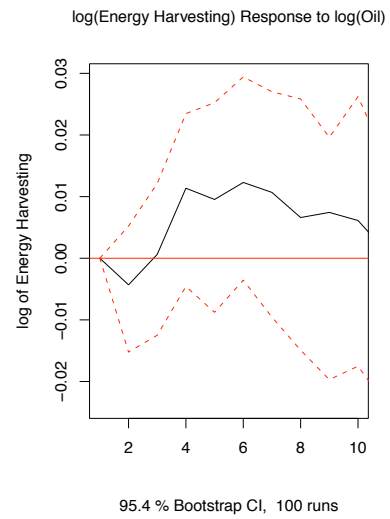
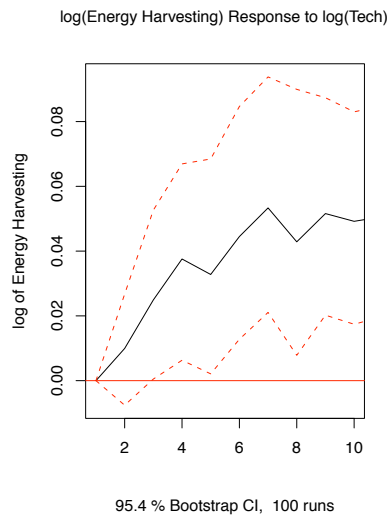
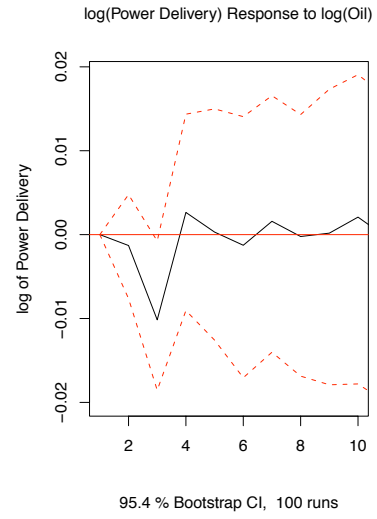
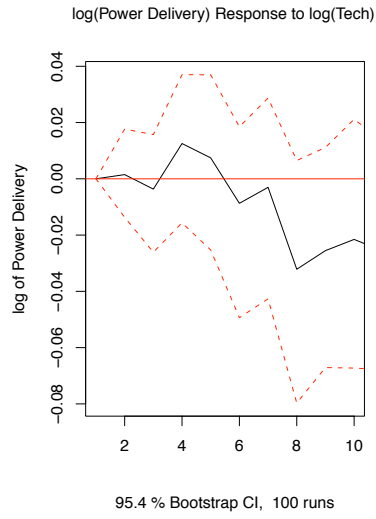


95.4 % Bootstrap CI, 100 runs

log(Energy Storage) Response to log(Oil)



95.4 % Bootstrap CI, 100 runs



Conclusions

The prices of alternative energy companies react to many complex economic stimuli. The performance of oil, the dominant conventional energy, is often seen to be predictive of the future alternative energy performance. This paper, using a vector autoregression model, investigated the validity of this assumption of oil's importance. In doing so, we extended the comparison between oil price and technology stock performance in the predictive power on alternative energy stock performance. We did so by splitting alternative energy into groups of stocks each with different places in the marketplace. Their respective places in the marketplace led us to suspect that their relationships with the predictor variables would be varied, and we found this to be the case.

This paper showed that, as in the original paper, the ECO index was more responsive to movements in technology stock performance than oil, and several of the breakdown indices followed suit (Harvesting, Storage, Cleaner Fuels, and Delivery, with Delivery showing a negative response to a technology shock) and some others showed opposite reactions, that is to say, a greater responsiveness to oil than technology (Greener Utilities and Energy Conversion).

Appendix A

The Barlett kernel for the PP and KPSS regressions are determined using the NeweyWest bandwidth (NWBW). All unit root tests regressions include an intercept, and are performed for up to 15 lags.

Three, two, or one asterisk denote significance at the one, five, or ten percent level.

0.1 Phillips/Perron Tests

lags	LGREEN	LCONV	LCLEAN	LSTOR	LDEL	LHARV
1	-2.0123	-2.8338*	-0.8304	-0.0438	-1.157	-.6031
2	-2.0079	-2.8427*	-0.7886	-0.0568	-1.1198	-.5425
3	-2.0062	-2.8897**	-0.7488	-0.1007	-1.2069	-.5771
4	-2.0069	-2.9023**	-0.7009	-0.1154	-1.2053	-.5703
5	-2.008	-2.926**	-0.6966	-0.1388	-1.2653	-.5975
6	-2.01	-2.9353**	-0.6738	-0.1608	-1.3134	-.6294
7	-2.0122	-2.9181**	-0.6418	-0.1785	-1.3211	-.6271
8	-2.0133	-2.9081**	-0.6275	-0.2061	-1.3294	-.6226
9	-2.0165	-2.8977**	-0.5943	-0.2276	-1.3192	-.6102
10	-2.0185	-2.8916**	-0.5642	-0.2409	-1.3133	-.6047
11	-2.0212	-2.8899**	-0.5441	-0.2462	-1.3218	-.6007
12	-2.0229	-2.8863**	-0.5135	-0.254	-1.32	-.5975
13	-2.0243	-2.8861**	-0.4935	-0.2729	-1.3068	-.5936
14	-2.0258	-2.8902**	-0.4874	-0.2955	-1.3019	-.5969
15	-2.0263	-2.8948**	-0.4718	-0.3201	-1.2799	-.5953

Table 12: PP Test

lags	LGREEN	LCONV	LCLEAN	LSTOR	LDEL	LHARV
1	-20.5345***	-19.5604***	-19.5604***	-16.3998***	-19.4898***	-20.98***
2	-20.5286***	-19.5871***	-19.5871***	-16.3734***	-19.493***	-21.0169***
3	-20.5199***	-19.6271***	-19.6271***	-16.4016***	-19.4594***	-20.9452***
4	-20.5005***	-19.6862***	-19.6862***	-16.4022***	-19.4587***	-20.9308***
5	-20.4778***	-19.6974***	-19.6974***	-16.4193***	-19.4521***	-20.8859***
6	-20.4576***	-19.7381***	-19.7381***	-16.4381***	-19.4537***	-20.8481***
7	-20.4417***	-19.7984***	-19.7984***	-16.4523***	-19.4536***	-20.847***
8	-20.4306***	-19.8346***	-19.8346***	-16.4844***	-19.4535***	-20.8541***
9	-20.4171***	-19.9162***	-19.9162***	-16.5108***	-19.4521***	-20.8692***
10	-20.4085***	-20.0057***	-20.0057***	-16.5272***	-19.4522***	-20.8793***
11	-20.4002***	-20.0807***	-20.0807***	-16.5315***	-19.4524***	-20.8874***
12	-20.3956***	-20.1877***	-20.1877***	-16.5399***	-19.4536***	-20.8952***
13	-20.3926***	-20.2669***	-20.2669***	-16.5677***	-19.4572***	-20.9032***
14	-20.3906***	-20.3052***	-20.3052***	-16.6024***	-19.4603***	-20.9037***
15	-20.3898***	-20.3774***	-20.3774***	-16.6432***	-19.47***	-20.9093***

Table 13: PP Test for First Differences

0.2 Kwiatkowski-Phillips-Schmidt-Shin Test

lags	LGREEN	LCONV	LCLEAN	LSTOR	LDEL	LHARV
1	3.6844***	2.2254***	14.2887***	9.302***	6.081***	8.5314***
2	2.47***	1.5022***	9.6022***	6.2281***	4.0934***	5.7135***
3	1.8615***	1.1407***	7.2559***	4.6901***	3.0968***	4.3025***
4	1.4963***	0.9246***	5.8473***	3.7673***	2.4997***	3.456***
5	1.2528***	0.781***	4.9074***	3.152***	2.1017***	2.8916***
6	1.079***	0.6789**	4.2358***	2.7126***	1.8182***	2.4888***
7	0.9488***	0.6026**	3.7318***	2.3831***	1.6061***	2.1869***
8	0.8475***	.5433**	3.3394***	2.127***	1.4415***	1.9523***
9	.7666***	.4958**	3.0252***	1.9221***	1.31***	1.7646***
10	.7005**	.4569*	2.7678***	1.7545***	1.2026***	1.611***
11	.6455**	.4244*	2.553***	1.6149***	1.1131***	1.483***
12	.599**	.3968*	2.371***	1.4968***	1.0374***	1.3747***
13	.5592**	.3732*	2.2149***	1.3955***	0.9726***	1.2818***
14	.5248**	.3527*	2.0796***	1.3078***	0.9163***	1.2012***
15	.4947**	.3348	1.961***	1.2312***	0.8671***	1.1307***

Table 14: KPSS Test

lags	LGREEN	LCONV	LCLEAN	LSTOR	LDEL	LHARV
1	.6426**	.213	.0484	.3663*	.2429	.3632*
2	.6693**	.2096	.0509	.3613*	.2535	.3933*
3	.6826**	.1908	.0534	.345	.2364	.3784*
4	.6804**	.1867	.0567	.3397	.2387	.3833*
5	.6756**	.1792	.0573	.3314	.228	.3721*
6	.6658**	.1766	.0591	.3238	.2201	.3591*
7	.6555**	.1824	.0617	.3178	.2203	.3617*
8	.6513**	.1863	.0631	.3088	.2204	.3653*
9	.6373**	.1905	.0661	.3019	.2242	.3726*
10	.6294**	.1934	.069	.2977	.2272	.3769*
11	.619**	.1948	.0711	.296	.2272	.3804*
12	.6126**	.1968	.0744	.2936	.2293	.3836*
13	.6073**	.1976	.0768	.2878	.234	.3873*
14	.602**	.1967	.078	.2811	.2369	.3873*
15	.5997**	.1954	.0801	.2741	.2439	.3898*

Table 15: KPSS Test for first differences

Citations

Henriques, I., and Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy. *Energy Economics* 30(3) 998-1010.

lags	LGREEN	LSTOR	LHARV
1	0.013	0.0038	0.003
2	0.0188	0.0064	0.0053
3	0.0254	0.0075	0.0057
4	0.0308	0.0102	0.0085
5	0.0364	0.0119	0.0097
6	0.0417	0.0137	0.0096
7	0.0455	0.017	0.0121
8	0.0543	0.0175	0.0132
9	0.0552	0.0188	0.0157
10	0.0625	0.0204	0.0169
11	0.0634	0.0241	0.0184
12	0.0689	0.0286	0.0197
13	0.0735	0.029	0.0226
14	0.075	0.0307	0.0221
15	0.0787	0.0314	0.0244

Table 16: KPSS Test for second differences